2012-03

Analyzing Navy Officer Inventory Projection Using Data Farming

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http://hdl.handle.net/10945/6868

NAVAL POSTGRADUATE SCHOOL

MONTEREY, CALIFORNIA

THESIS

ANALYZING NAVY OFFICER INVENTORY PROJECTION USING DATA FARMING

by

Christy N. Sibley

March 2012

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REPORT DOCUMENTATION PAGE	*Form Approved OMB No. 0704–0188*

Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instruction, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202–4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704–0188) Washington DC 20503.

1. AGENCY USE ONLY *(Leave blank)*	**2. REPORT DATE** March 2012	**3. REPORT TYPE AND DATES COVERED** Master's Thesis

4. TITLE AND SUBTITLE Analyzing Navy Officer Inventory Projection Using Data Farming	**5. FUNDING NUMBERS**
6. AUTHOR(S) Christy N. Sibley	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Naval Postgraduate School Monterey, CA 93943–5000	**8. PERFORMING ORGANIZATION REPORT NUMBER**
9. SPONSORING /MONITORING AGENCY NAME(S) AND ADDRESS(ES) Deputy Chief of Naval Operations (MPT&E) OPNAV N14 NSF-Arlington BLDG 12, 701 COURTHOUSE ROAD Arlington, VA 22204-2485	**10. SPONSORING/MONITORING AGENCY REPORT NUMBER**

11. SUPPLEMENTARY NOTES The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government. IRB Protocol: N/A.

12a. DISTRIBUTION / AVAILABILITY STATEMENT Approved for public release; distribution is unlimited	**12b. DISTRIBUTION CODE** A

13. ABSTRACT (maximum 200 words)

The Navy's Strategic Planning and Analysis Directorate (OPNAV N14) uses a complex model to project officer status in the coming years. The Officer Strategic Analysis Model (OSAM) projects officer status using an initial inventory, historical loss rates, and dependent functions for accessions, losses, lateral transfers, and promotions that reflect Navy policy and U.S. law. OSAM is a tool for informing decision makers as they consider potential policy changes, or analyze the impact of policy changes already in place, by generating Navy Officer inventory projections for a specified time horizon.

This research explores applications of data farming for potential improvement of OSAM. An analysis of OSAM inventory forecast variations over a large number of scenarios while changing multiple input parameters enables assessment of key inputs. This research explores OSAM through applying the principles of design of experiments, regression modeling, and nonlinear programming. The objectives of this portion of the work include identifying critical parameters, determining a suitable measure of effectiveness, assessing model sensitivities, evaluating performance across a spectrum of loss adjustment factors, and determining appropriate values of key model inputs for future use in forecasting Navy officer inventory.

14. SUBJECT TERMS data farming, design of experiments, manpower, officer inventory, manning forecast	**15. NUMBER OF PAGES** 84
	16. PRICE CODE

17. SECURITY CLASSIFICATION OF REPORT	**18. SECURITY CLASSIFICATION OF THIS PAGE**	**19. SECURITY CLASSIFICATION OF ABSTRACT**	**20. LIMITATION OF ABSTRACT**
Unclassified	Unclassified	Unclassified	UU

NSN 7540–01–280–5500

Standard Form 298 (Rev. 8–98)
Prescribed by ANSI Std. Z39.18

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ANALYZING NAVY OFFICER INVENTORY PROJECTION USING DATA FARMING

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Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

NAVAL POSTGRADUATE SCHOOL
MARCH 2012

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The Navy's Strategic Planning and Analysis Directorate (OPNAV N14) uses a complex model to project officer status in the coming years. The Officer Strategic Analysis Model (OSAM) projects officer status using an initial inventory, historical loss rates, and dependent functions for accessions, losses, lateral transfers, and promotions that reflect Navy policy and U.S. law. OSAM is a tool for informing decision makers as they consider potential policy changes, or analyze the impact of policy changes already in place, by generating Navy Officer inventory projections for a specified time horizon.

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LIST OF ACRONYMS AND ABBREVIATIONS

902x	Surface Warfare Officer declined for lateral transfer
AGR	Active Guard Reserve
AIC	Akaike's Information Criterion
ASCAR	Accession Supply Costing and Requirements
CI	Confidence Interval
CNA	Center for Naval Analyses
CNO	Chief of Naval Operations
DoD	Department of Defense
DOE	Design of Experiments
DOPMA	Defense Officer Personnel Management Act
DP	Design point
ES	Enlisted Specialty
FY	Fiscal year
FYDP	Fiscal Year Defense Plan
GR	Grade
HR	Human Resources
LB	Lower Bound
LDO	Limited Duty Officer
LH	Latin hypercube
MAPE	Mean absolute proportional error
MSC	Medical Service Corps
N1	Chief of Naval Personnel
NOLH	Nearly orthogonal Latin hypercube
NPS	Naval Postgraduate School
NROTC	Naval Reserve Officer Training Corps
OPA	Officer Programmed Authorization
OPNAV N14	Navy's Strategic Planning and Analysis Directorate
OSAM	Officer Strategic Analysis Model
POM	Program Objective Memorandum
RCMOP	Requirements-Driven Cost-Based Manpower Optimization
RL	Restricted Line
SEED	Simulation Experiments & Efficient Designs
SK	Skill
SWO	Surface Warfare Officer
UB	Upper Bound
U.S.	United States
URL	Unrestricted Line
VFP9	Visual Fox Pro Version 9
YCS	Years of Commissioned Service

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EXECUTIVE SUMMARY

Manpower and personnel costs consume a significant portion of the U.S. Navy budget every year, and Navy planners face the challenge of balancing manpower requirements and mandated end strength with budget constraints. The variability of human behavior further complicates the issue of forecasting strength. The Chief of Naval Personnel's (N1's) Strategic Resourcing Branch is responsible for analyzing manpower inventory forecasts and estimating the Navy's manpower expenditures to be included in the budget and Program Objectives Memorandum (POM) submitted to the Secretary of the Navy every two years. Forecasting Navy Officer inventory is a complex problem with an imperfect solution. One tool currently in use to tackle this problem is the Officer Strategic Analysis Model (OSAM), a model that follows individual officers from an initial inventory, or entities, through possible attribute changes during a forecast period, resulting in a projection of status for each officer in the coming years. OSAM is a tool for informing decision makers as they consider potential policy changes, or analyzing the impact of policy changes already in place, by generating Navy officer inventory projections for a specified time horizon.

Navy officer inventory changes continuously, but decision makers find it useful to have accurate information about annual variations in inventory; this is what OSAM models. The key attributes of rank, designator, time-in-service, and time-in-grade describe each officer in inventory and adjust as time elapses. In addition to initial inventory, functions describing accession, promotion, lateral transfer, and loss influence the total officer inventory characterization. To model losses, OSAM multiplies historical loss rates by a loss adjustment factor for each category of officers. The model is capable of assigning a unique loss adjustment factor for each combination of key attributes, but recent practice is to apply the same loss adjustment factor universally to all designators and grades in a given projection year (i.e., loss adjustment factor = 1.041 in year two, 1.059 in year three, 1.085 in year four, 1.114 in year five). These values describe a set of

typical loss adjustment factors that OPNAV N14 provided to model a slowly improving economy. The thesis work presented here analyzes OSAM using designs of experiments and simulation analysis to explore the capabilities and limitations of the model, specifically targeting the lateral transfer and loss functions within the model.

Deployment of OSAM on Naval Postgraduate School (NPS) computers enables exploitation of multiple processors and advanced statistical methods of analysis. Several different analytical methods provide insights into OSAM. Final analysis results in recommended loss adjustment factors that generate a better forecast than past practice, at a 90% confidence level. An OSAM modification allows the tracking of loss behavior of Surface Warfare Officers (SWOs) whose lateral transfer efforts are unsuccessful. Analysis of experiments reveals that these officers' loss adjustment factors are the same as SWOs who never applied for lateral transfer, at a 95% confidence level. Additional experiments are necessary to determine whether there is a benefit to modeling these officers separately, as this OSAM modification allows a unique historical loss rate to enter the model.

This thesis compares OSAM forecasts to historical inventories over a five year period, and results could potentially improve with additional base year data available. Extension of this analysis over a broader time frame may also capture the impact of varying political and economic environments. This first foray into data farming OSAM studies only two officer communities, including four designators. Recommendations for future research include variation of additional parameters in future designs of experiments, and focused analysis on individual community forecasts, independently or in conjunction with other communities or the overall officer inventory. A weighted approach to such an analysis can require satisfaction of absolute requirements while observing flexibility in the officer inventory distribution according to anticipated behavior.

ACKNOWLEDGMENTS

I would like to thank Dr. Horne for guiding me in my pursuit of analytical research in the field of Navy manpower. Dr. Horne's perpetual and infectious enthusiasm, as well as his unwavering support in the face of challenges, enabled me to select a thesis topic and conduct research that has real value to the Navy and to the Human Resources Community. I would like to thank MAJ Seagren for his analytical guidance, and editorial acumen, and for being available anytime I needed to brainstorm or discuss quick questions. Each of you contributed to my work in varying ways, and I am lucky to have you both as my advisors. I would like to thank OPNAV N14 for support and funding, and in particular Paul Soutter for teaching me everything I needed to know about OSAM, implementing changes in OSAM to assist my research efforts, and being constantly available as a sounding board to ensure I fully understand the implications of OSAM forecasts. Everyone at OPNAV N14 has been a joy to work with on this project. I would like to thank Steve Upton for implementing OSAM in a data farming environment, and always providing a rapid turnaround of experimental results, even during the Christmas holidays. Most importantly, I would like to thank my husband, Paul, for his moral support and commitment during this challenging, but valuable educational experience.

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I. INTRODUCTION

A. PROBLEM STATEMENT

Manpower and personnel costs consume a significant portion of the U.S. Navy budget every year, and Navy planners face the challenge of balancing manpower requirements and mandated end strength with budget constraints. The variability of human behavior further complicates the issue of forecasting strength. The Chief of Naval Personnel's (N1's) Strategic Resourcing Branch is responsible for analyzing manpower inventory forecasts and estimating the Navy's manpower expenditures to be included in the budget and Program Objectives Memorandum (POM) submitted to the Secretary of the Navy every two years. Forecasting Navy Officer inventory is a complex problem with an imperfect solution. One tool currently in use to tackle this problem is the Officer Strategic Analysis Model (OSAM), an entity based model that follows individual officers, or entities, from an initial inventory through possible attribute changes during a forecast period, resulting in a projection of status for each officer in the coming years. OSAM is not a tool for predicting budgetary expenses, but rather for informing decision makers as they consider potential policy changes, or analyzing the impact of policy changes already in place, by generating Navy officer inventory projections for a specified time horizon.

In its current form, OSAM is complicated to use and limited to small-scale employment. Prior to conduct of this research, OSAM had not been analyzed for variations over a large number of scenarios while changing multiple input parameters. The application of data farming methodology to the exploration of OSAM enhances understanding of the model's capabilities and limitations. This thesis focuses on identifying effective means of applying data farming tools to OSAM exploration while targeting specific research questions related to the loss and lateral transfer functions of the model.

B. PURPOSE

This study determines whether an adaptation of the OSAM currently in use by the Navy's Strategic Planning and Analysis Directorate (OPNAV N14) could more effectively inform decisions about future loss rates and lateral transfers. OSAM forecasts are particularly sensitive to changes in projected loss rates, and there is not an accurate means to project loss rates. A robust design of experiments and iterative data analysis results in a better understanding of how variations in specific loss rates and lateral transfer rates affect OSAM inventory forecasts. Application of these methods to OSAM yield a more beneficial planning tool for decision makers.

There is a great deal of interest in retention strategies for specific communities, in addition to officer retention in the combined officer corps. Lateral transfers are essential to staff communities that have no direct accession sources, and to retain talented leaders that otherwise might leave the Navy altogether. This study assesses the sensitivity of OSAM to variations in loss rate projections and lateral transfer rates, and suggests a systematic approach for future researchers to apply to additional questions.

An additional product of this research is the modification of OSAM scenario management for a more efficient and user-friendly interface. Automated model implementation for data farming opens up a wealth of future research opportunities. Extending these tools to examination of additional aspects of officer inventory management may lead to improved community management, accession planning, promotion planning, and loss rate projections.

C. RESEARCH QUESTIONS

Navy officer inventory changes continuously, while long-term planning relies on effective personnel forecasting to influence key decisions. OSAM fills an essential role for Navy planners by modeling the Navy officer component of personnel forecasting. In this model, the key attributes of rank, designator, time-

in-service, and time-in-grade describe each officer in inventory and adjust as time elapses. In addition to initial inventory, functions describing accession, promotion, lateral transfer, and loss influence the total officer inventory characterization. This research focuses on the outcome of lateral transfers and losses on Navy Officer inventory projections by addressing three specific research questions:

- What is a reasonable range of loss adjustment factors to use in OSAM for accurate officer inventory projections?
- How sensitive are officer inventory projections to varying future loss rates for specific communities or pay grades?
- Is there a forecasting benefit to adjusting loss rates differently for officers who applied for lateral transfer and were declined, compared to officers who never applied for lateral transfer?

In answering these research questions, the application of specific hypothesis tests yields insight to analytical results. These hypotheses, discussed at length in Chapter IV, are:

- Primary hypothesis 1: The forecast generated from experimentally determined loss adjustment factors is more accurate than a forecast generated from a set of loss adjustment factors in which all values are 1.0.
- Primary hypothesis 2: The forecast generated from experimentally determined loss adjustment factors is more accurate than a forecast generated from a set of loss adjustment factors in which values for projection year one are equal to 1.0, year two values are 1.041, year three values are 1.059, year four values are 1.085, and year five values are 1.114. These values describe a set of typical loss adjustment factors that OPNAV N14 provided to model a slowly improving economy.

- Secondary hypothesis: Applying the unique set of loss adjustment factors for 902x officers, SWOs with declined lateral transfer applications, determined from a rigorous analysis yields a more accurate forecast than applying SWO loss adjustment factors to these declined lateral transfer applicants.

D. SCOPE AND METHODOLOGY

This study examines Navy officer inventory projection using the three research questions. Automation of input parameter adjustment and the post-processing of results enabled an approach to the research questions in the context of data farming. Analysis of preliminary experiments identifies the loss rates with a significant impact on OSAM forecast accuracy and narrows the relevant range of these loss rates, resulting in a more compact design space for the next set of experiments. Selection of the final design space maximizes the information obtained about the model within the constraints of available time and computing power.

OPNAV N14 enhanced OSAM to track lateral transfer applicants not selected for transfer, assigning a distinct loss rate to these officers. Analysis of preliminary and final experiments compares experimental results to historical data to determine whether the change to OSAM for tracking lateral transfer applicants results in more accurate officer inventory projections. Additionally, experiments conducted for various loss rates were compared to historical data to determine what range of loss adjustment factors should be used by OSAM operators in future scenario consideration. Ultimately, this study demonstrates the value of OSAM and its potential analytical products in a data farming environment.

E. ORGANIZATION OF THESIS

This thesis contains five chapters. Chapter II presents a brief overview of the current Navy Officer manpower planning process, the role of Officer Strategic Analysis Model (OSAM) in personnel policy decisions, and how data farming can multiply the power of OSAM as a tool for Navy decision makers. Chapter II also reviews manpower inventory projection related literature. Chapter III presents the design of experiments employed in data farming OSAM, and discusses the methodology of the data farming process. Chapter IV presents the analysis of experimental results. Chapter V reports conclusions and recommendations for future research.

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II. BACKGROUND

This chapter develops the foundation necessary to understand the importance of this thesis to United States Navy decision makers. In addition to defining the Navy officer manpower environment and reviewing past research conducted in this field, the background contained herein provides context to the methodology and results detailed in later chapters.

A. NAVY OFFICER MANPOWER

A key component of budgeting is accurately predicting manpower inventory in a dynamic environment subject to both organizational policies and the desires of individuals within the system. Officer inventory is particularly difficult to predict, as personnel may enter the system at multiple ranks, can choose to move between specialties at numerous points in a career, and there is no proven means to predict officer loss rates.

U.S. Code, Title 10 regulates original appointments for commissioned officers (Section 33), specifies the control of officers above the grade of O-3 (Section 32), and governs aspects of officer promotions, separations, and involuntary retirements for all United States military branches (Section 36). Title 10 codifies some facets of the Defense Officer Personnel Management Act (DOPMA), passed into law in 1980. In addition to aspects of DOPMA written into law, Department of Defense (DoD) policies derived from Congressional intent supplementing DOPMA legislation provide guidelines on promotion flow points and desirable minimum promotion opportunity for officers in each pay grade. (Schirmer et al., 2006)

Officer career progression occurs upwardly via promotions, and sometimes laterally via redesignation. Lateral transfers between Navy officer communities potentially improve retention and career satisfaction for individuals, and enhances the ability of the Navy to staff officer communities properly when

unexpected shortfalls occur. According to Chief of Navy Operations (CNO) Instruction (OPNAVINST 1210.5), dated 24 Dec 2005, the purpose of lateral transfers is “to provide flexibility in the manning of officer communities.” This policy offers flexibility to the Navy, but also to individual officers, and adds additional uncertainty to the prediction of loss rates for applying officers denied the opportunity to transfer.

Officer inventory projection models incorporate the key elements of officer career management and progression described here. Such models provide allowances for deviations from policies and practices to enable evaluation of policy changes, while intractable rules integrate laws into the modeling environment. A quick reference guide published for the Strategic Planning and Analysis Directorate (OPNAV N14) delineates which aspects of personnel management meet law, which satisfy policy, and which implement common practice (Yardley et al., 2005).

B. OFFICER STRATEGIC ANALYS IS MODEL (OSAM)

1. Overview of the Model

OPNAV N14 uses OSAM to project inventory of the active duty Navy Officer Corps over the time horizon of the Officer Programmed Authorization (OPA). The OPA specifies how many officers of each grade (Ensign through Captain) are required in each designator (73 skill sets modeled) in each projection year across the Fiscal Year Defense Plan (FYDP), which extends six years into the future. OSAM is an entity based model, maintaining designator, grade, and time-in-service information for individual officers, current and projected. By modeling officer behavior consistent with how the Navy Officer Corps behaves, OSAM attempts to generate a supply of officers with the right skills in the right grades at the right times.

The purpose of OSAM is to predict on a yearly basis the grade, skill, and time-in-service (or years of commissioned service) content of the Active Navy

Officer force. In the model, four inter-related functions influence expected outcomes: loss generation, promotions, lateral transfers, and accessions. User-defined parameters affect each of these functions, and they influence each other through interactions within the model. One objective of OSAM is to inform policy decisions by generating specific scenarios on request for decision makers. For instance, if Navy Recruiting Command needs to know whether their current accessions plan, in combination with NROTC and Naval Academy accessions, will be sufficient to supply the warfare communities with the required lieutenants in four years, OSAM can execute a scenario with the given accession plan to answer this question. A user-defined setting determines whether OSAM runs constrained to the inventory set by OPA for each year, or unconstrained to observe how officer inventory behaves on its own. The output of OSAM is a complete inventory of officers at the end of each projection year, characterized by the attributes of grade, designator, date of rank, time-in-service, and years of commissioned service.

OSAM has great potential to inform policy makers, but it has many weaknesses as well. As a deterministic model, OSAM provides no confidence intervals for the officer inventory projected by its unconstrained mode. Furthermore, OSAM utilizes four interdependent functions to generate final output, and the interactions between these function may change from projection year to projection year. Of these four functions, promotions and accessions closely reflect Navy policies and behaviors. The promotion function is modeled three different ways, with user input determining the model to use in a given scenario; the default option is to promote to vacancy, as this is the underlying Navy policy. A known accession plan models officer gains for the first projection year, and in subsequent years new accessions are either unconstrained (determining according to the promotions, losses, and lateral transfers) or constrained so that officer end strength equals OPA. Promotion and accession functions in OSAM closely reflect the policies and practices implemented by Navy decision makers. Losses and lateral transfers are functions that depend

heavily on the unpredictable behavior and personal decisions of individual officers. The focus of this research is on the OSAM functions for loss rates and lateral transfers, intending to identify model parameters than will accurately capture the average behavior of individuals.

2. Modeling Officer Loss Rates

OSAM operators at OPNAV N14 note that the most significant unknown factor on model output is loss rates for projection years. Model output appears more sensitive to changes in loss rates than to other parameters, yet there is no good prediction system for officer loss rates from the Navy (as opposed to enlisted loss rates, which are correlated closely with unemployment rates). OSAM generates losses in two ways: regular loss rates reflect officers leaving the Navy by personal choice or policy reasons, and forced loss rates reflect the practice of from active service if twice non-selected for promotion. For any scenario, a user can also elect to turn on or off the force out business rules, potentially informing decisions on when and how often to allow exceptions to that rule.

OSAM generates regular loss rates by multiplying historical loss rates (either most recent year baseline or a three-year average from the preceding three years) for a particular designator/rank/time-in-service combination by a loss adjustment factor defined by the OSAM user. For a particular designator/rank/time-in-service combination, the loss adjustment factor for a given projection year is equal to 1.0 if the analyst believes losses in that projection year will be exactly equal to historical losses. The adjustment factor will be less than 1.0 if the analyst believes the losses will be less than historical losses, and greater than 1.0 if the expected losses are greater than historical losses. Without a clear prediction formula for officer loss rates in future years, a working set of parameters for hypothesis testing is to apply the same loss adjustment factor universally to all designators and grades in a given projection year (i.e., loss adjustment factor = 1.041 in year two, 1.059 in year three, 1.085 in

year four, 1.114 in year five). These values describe a set of typical loss adjustment factors that OPNAV N14 provided to model a slowly improving economy.

Each scenario implemented in OSAM has 2,025 loss adjustment factors as inputs to the model. Prior to this research, common practice applied the same loss adjustment factor to all officers in a given projection year, when in fact the loss rates of pilots five years from now may have changed differently than the loss rates of intelligence officers. While the loss adjustment factors used are reasonable values based on the experience of OSAM designers and users, it is desirable to know just how sensitive the model is to these changes. Data farming provides an opportunity to observe a variety of loss rates in a range, and to consider how varying loss rates differently for individual designator and grade combinations could affect total officer inventory and individual community inventory.

With access to the actual Navy officer inventory data for every fiscal year since 1978, it is feasible to select multiple start years, and use OSAM to project FYDP inventory with various loss adjustment factors, then compare projections to the actual historical inventories in projected years. Rather than varying all 2,025 loss rates, this research focuses on surface warfare officers (SWOs) and human resources (HR) officers.

A third designator, 902x, created in OSAM to support this research, represents SWOs declined an opportunity to lateral transfer. Past research has shown that these officers have a significantly higher probability of leaving the Navy than SWOs who successfully lateral transfer or never apply for a lateral transfer (Kleyman & Parcell, 2010). Each officer modeled in OSAM belongs to only one community at a time. In reality, 902x officers as defined for this research are a subset of the SWO community, but in OSAM these two groups are disjoint sets. Even limiting variation of loss adjustment factors to these three categories, each design point includes 90 variables representing a unique loss adjustment factor in OSAM. A preliminary design of experiments determines which loss rates

are most useful to vary, and subsequent iterations further narrow the range of loss rates appropriate to use in forecasting officer inventory over multiple start years.

3. Modeling Lateral Transfers

There are three types of lateral transfers modeled in OSAM: training attrites, option officers, and lateral transfers. Training attrites are officers who do not complete initial training in their original designator. Option officers enter the Navy with a contract specifying a lateral transfer to occur after completing surface warfare officer qualification. The transfer behavior of these two groups is explicitly modeled in a user defined input file; an OSAM user can specify how officers move among designators via the lateral transfer application process, but the typical user setting is to leave lateral transfer behavior unconstrained, letting OSAM calculate the correct number. In this case, OSAM determines the number of officers required to supply lateral transfers to recipient communities. Each supplying community supplies a fraction of all its officers eligible for lateral transfer such that each community supplies a similar proportion of its whole. Notably, there is no restriction modeled in OSAM on the number of officers taken from each supplying community, which could potentially leave one or more of these supplying communities short of senior officers in a future projection year.

A 2010 study of the lateral transfer application process by Center for Naval Analyses (CNA) observes that 41% of applicants disapproved for lateral transfer leave the Navy within 36 months, while only 10% of applicants approved for lateral transfer leave the Navy within 36 months. (Kleyman & Parcell) Currently, OSAM does not model the lateral transfer application process itself, only the change in designator for the officers approved to transfer. The findings of CNA could have a significant impact on the total Navy officer inventory and in particular on specific officer communities. Kleyman and Parcell's (2010) study consider the applicants to lateral transfer boards in the period between 2005 and 2010. If applied to an improved OSAM model, their findings enable comparison

of OSAM forecasts for multiple start years to the original OSAM model projections, and to the actual observed historical inventories.

4. Goals of the Model

“All models are wrong, but some are useful” (Box & Draper, 1987). OSAM is a complex model used to observe the results of “What if?” scenarios for Navy planners. At this time, OSAM is a Microsoft Visual FoxPro 9.0 executable application, dependent on input contained in 60 database files. A baseline scenario draws information from each of these files, and adjustments to the baseline scenarios occur via individually editing one or more of the 60 input files. A Microsoft Word document maintained with each set of database files tracks specific parameters defined in the database files. Generating a new scenario involves meticulous attention to detail in adjusting the database files and documenting the changes. Some methods employed to reduce human error when using this complex scenario management system are repetition and consistent practices. There is a single employee at OPNAV N14 whose primary job is to track and maintain OSAM scenarios, and to run new scenarios as needed. Even this experienced individual requires fifteen to twenty minutes to prepare and document a well-defined scenario. The run itself takes 3–12 minutes, depending on the machine resources available. Output analysis, primarily visualization in pivot charts, occurs immediately after running a scenario and takes 15–30 minutes, depending on the number and types of questions of interest. Despite complexities in implementation, OSAM is a powerful tool with great potential for informing Navy leadership on the impacts of proposed policy changes.

This thesis, in conjunction with the Simulation Experiments & Efficient Designs (SEED) Center for Data Farming, considers different choices of input parameters to OSAM within reasonable ranges, performs sensitivity analysis on these parameters, and suggests reasonable values or ranges of values to use as inputs to OSAM. Preliminary analysis determines reasonable ranges of variation

for ninety loss adjustment factors. The input to OSAM that has the greatest influence on results is loss rates, for which there is no reliable prediction means at this time. The ability to execute numerous runs of OSAM in a short period in a data farming environment provides an opportunity to understand the impact of varying loss rates on officer inventory.

C. LITERATURE REVIEW

For as long as there have been organizations, managers have had an interest in predicting the flow of manpower into, within, and out of them; military leaders have faced this challenge for as long as armies have been around. This need for leaders to plan ahead evolved over time to simple manpower modeling and then to multifaceted projection planning as the size and complexity of organizations expanded over the centuries. Manpower modeling in general and military manpower modeling in particular has been the subject of targeted operations research since before operations research has been a recognized discipline. As availability of computing power has improved dramatically, manpower modeling has reached new levels of complexity; the research conducted over the past few decades has laid a solid foundation for the Officer Strategic Analysis Model examined in this thesis.

A review of literature previously published on the subject of manpower modeling provides background information on the subject, identifies successful model explorations, and highlights limitations of previous studies in the context of this thesis. Publications on the subject of manpower modeling are numerous, but none apply data farming tools to exploring an existing officer manpower model. This literature review identifies research on similar or related topics, such as developing new officer inventory models, or data farming an existing enlisted manpower model. Despite the significant gap between this thesis and previously published works, each of the sources identified in this literature review provide background and context to the evolving field of forecasting military personnel accurately.

The results of this literature review cover two distinct topics: Navy manpower modeling, and other service manpower modeling. The discussion on Navy manpower modeling falls under the subdivisions of inventory projection research and studies targeting lateral transfer processes and loss rate projections.

1. Navy Manpower Modeling

a. Inventory Projection

One definition of manpower planning is the interaction of three processes: predicting future demand, predicting future supply, and evaluating policies intended to bring predicted demand and predicted supply as close together as possible (Edwards, 1983). Inventory projection brings together all three of these functions by using organizational knowledge and policies to predict supply and demand, and observing the gap between them. Each inventory projection model considered in this literature review has the ultimate goal of informing decision makers on the impact of potential policy changes.

Clark (2009) develops a linear optimization program, Requirements-Driven Cost-Based Manpower Optimization (RCMOP), to project monthly values for Navy officer inventory by minimizing unmet manpower requirements without over-executing the budget. Like OSAM, Clark (2009) models officer inventory as a function of four component functions: promotions, accessions, lateral transfers, and losses. RCMOP assigns penalties to unmet manpower requirements to determine priority in executing the budget, while OSAM can either constrain inventory to meet manpower requirements or allow the officer inventory to progress naturally according to expected behavior of individuals if unconstrained by OPA.

Wheeler (2010) builds on Clark’s 2009 RCMOP model. Wheeler considers variation of loss rates and additional officer communities, as well as increasing the time horizon considered. The majority of officer communities

remain in the “other” category under Wheeler’s analysis. The nature of OSAM as a simulation model allows incorporation of each Navy officer community separately to obtain high-resolution inventory. Clark (2009) and Wheeler (2010) focus on meeting budget requirements, a goal distinctly different from that of this research, which focuses on assessing the treatment of loss rates employed in generating an accurate forecast.

b. Lateral Transfer Modeling or Analysis

In 1997, the Center for Navy Analyses (CNA) examines the Navy’s lateral transfer system. Moore and Reese (1997) assess how the policy of staffing Restricted Line (RL) and Staff Corps communities fit into a strategy to increase retention and career satisfaction among officer. At the time of Moore and Reese’s study, there is a shortage of lateral transfers to sustain the RL and Staff communities; a secondary goal of their research is to determine whether an adjustment to transfer rates is appropriate. This CNA study observes that lateral transfer arising from training attrition early in an officer’s career fail to obtain warfare qualification more often than officers originally placed in a designator do; Moore and Reese suggest that this is due to a mismatch between the job and the officer. The observations in this 1997 analysis lay the foundation for numerous studies on the subject of lateral transfers in subsequent years, but do not attempt to model lateral transfers in a forecasting environment.

In 2004, Monroe and Cymrot analyze a proposed policy of cutting Navy officer accessions and limiting lateral transfers, ultimately determining that reducing Surface Warfare Officer (SWO) accessions by 160 officers each year could save the Navy $91 million. This study considers only the SWO community, using productivity measures to estimate the tradeoffs between keeping officers in the SWO community and allowing them to transfer in greater numbers to RL or Staff communities. Generally, any SWO queried in an unofficial context will state that fellow SWOs pursuing a lateral transfer and declined the opportunity to transfer often elect to leave the Navy, thus still creating a gap in SWO

manpower. Monroe and Cymrot (2004) take steps to quantify these choices by SWOs, and lay the groundwork for future studies to drill down further. Monroe and Cymrot do not address the questions undertaken in this thesis, but nonetheless provide background important to understanding and interpreting forecast results.

In 2007, Ryan identifies factors that lead Unrestricted Line (URL) officers to request lateral transfers, identifies lateral transfer selection criteria used by selection boards, and determines through regression analysis that officers turned down by a lateral transfer selection board have a different retention likelihood than officers who apply and are selected. “Officers who apply for lateral transfer but are not selected are more than twice as likely to leave the Navy as those who are selected” (Ryan, 2007, p. 73). Ryan’s research does not quantify the impact of his findings on inventory projections, as this thesis begins to do.

Building on Ryan’s 2007 work, Kleyman and Parcell (2010) conduct a thorough statistical analysis of lateral transfer applicants over a five-year period, and determine a lower bound impact of denying applicants solely based on supplying community quotas. Ryan (2007) and Kleyman and Parcell (2010) note retention differences, but stop short of applying these differences to modeling loss rates for lateral transfer applicants, a task uniquely suited to data farming an inventory projection model such as OSAM.

2. Other Service Manpower Modeling

In 1983, a simulation model for military personnel analysis, the Accession Supply Costing and Requirements (ASCAR) model, develops to compute projected shortfalls in desired end strength and total man-years (Collins et al., 1983). This model, like OSAM, informs decision makers on the impact of potential personnel policies. This model is an important predecessor to OSAM in both its design and its purpose, but as a model for active duty enlisted personnel,

ASCAR does not consider the complexities of prior service and promotions in controlled grades, which this thesis must incorporate in the analysis of officer inventory projections.

In 1991, Grant publishes a special report discussing a non-line officer projection model developed for the United States Air Force to inform the effect of policy decisions, such as compensation and promotion adjustments, on future force structure. This model is an discrete event simulation and includes many of the functional aspects that OSAM addresses, though there is no allowance for lateral transfers in this Air Force model. Notably, the non-line officer projection model presented by Grant (1991) does not consider the non-line officer force as an aggregate. That is, the model provides a forecast for each officer community in isolation, thus missing any interaction effects that affect the total force.

Fiebrandt (1993) develops and implements a U.S. Coast Guard Rating Forecast Model to project inventory and personnel flow by rating. Though this model is for enlisted personnel and for a different military service, it treats functions similarly to OSAM, though the constraints behave differently. The greatest shortcoming of Fiebrandt’s model in the context of officer inventory projection is that, like Grant (1991), it models only one community at a time, losing the information gained from observing redesignations between ratings.

In 2002, Schrews develops a new optimization model for enlisted manpower projection in the United States Army Active Guard Reserve (AGR). The model developed by Schrews (2002) tracks soldiers through a simulation with the same attributes that OSAM follows, and deals with accessions at pay grades E-4 to E-9, rather than at the initial training point. Though Schrews (2002) does address loss rate variations, these variations have a small impact on results, as new gains to the system replacing losses require only a one-week training pipeline. OSAM must incorporate training pipelines from 6 months to 8 years for different designators, so the effect of loss rates on forecasts warrants rigorous analysis.

Erdman (2010) uses experimental design and data analysis to study the U.S. Army's Enlisted Specialty (ES) model. The ES model uses coefficients to set penalties and rewards on different components of its objective function; the user can adjust these coefficients to focus the optimization on certain goals to observe the impact on future decisions. Erdman's 2010 thesis uses data farming to select the coefficient values that had the greatest impact on lowering the deviation between inventory and authorizations over the planning horizon. Like OSAM, the ES model projects manpower inventory in specific job types and ranks. While the modeling methods employed are very different between the two (entity-based simulation in OSAM vs. linear optimization in ES model), the applicability of data farming is similar for each. The use of historical data as a representation of the future to assess input parameter values is important to this thesis, as it was in assessing the ES model.

While the studies reviewed in this chapter each provide insight to the intricacies of Navy officer manpower modeling, none of them addressed the issue of modeling all officers in a service, accounting for individual communities and transition between them. OSAM's capability to handle these complexities is unique. With this fact in mind, the application of an effective design of experiments, data farming, and simulation analysis to OSAM is the subject of the remaining chapters in this thesis.

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III. METHODOLOGY AND APPROACH

This chapter introduces the tools and methods employed in gathering, processing, and analyzing data from 495 OSAM simulations. Each simulation produces about 80,000 rows of data, each of which represents a Navy officer in a given year. The selection of experimental designs and the reduction of generated data to a single measure of effectiveness presents a unique challenge. This chapter discusses analytical methods used is assessing the forecast accuracy of OSAM.

A. DATA FARMING

1. Definition and Application

Data farming is a continually evolving combination of methods that capitalizes on high performance computing to explore a decision space more completely than traditional analytics typically allow. The opportunity to observe an entire landscape of solutions enables analysts to interpret results, assess model validity, identify and examine outliers, and explore otherwise insurmountable research questions (Horne & Meyer, 2010).

Any model with multiple input parameters subject to variation could be a candidate for data farming. Efficient experimental design combined with automation of input parameter variations can leverage high performance computing to explore a large design space (Horne & Schwierz, 2008). Figure 1 depicts the iterative nature of data farming. The scenario building loop in Figure 1 includes building a model and defining research questions to explore with that model. This research uses a pre-built model, OSAM, so this scenario building loop refers to the specification of research questions and determination of how to proceed with model exploration. The scenario run space execution loop on the right hand side of Figure 1 describes the process of designating a design space,

executing multiple experiments, analyzing and interpreting results, and repeating the process as appropriate (Horne & Meyer, 2004).

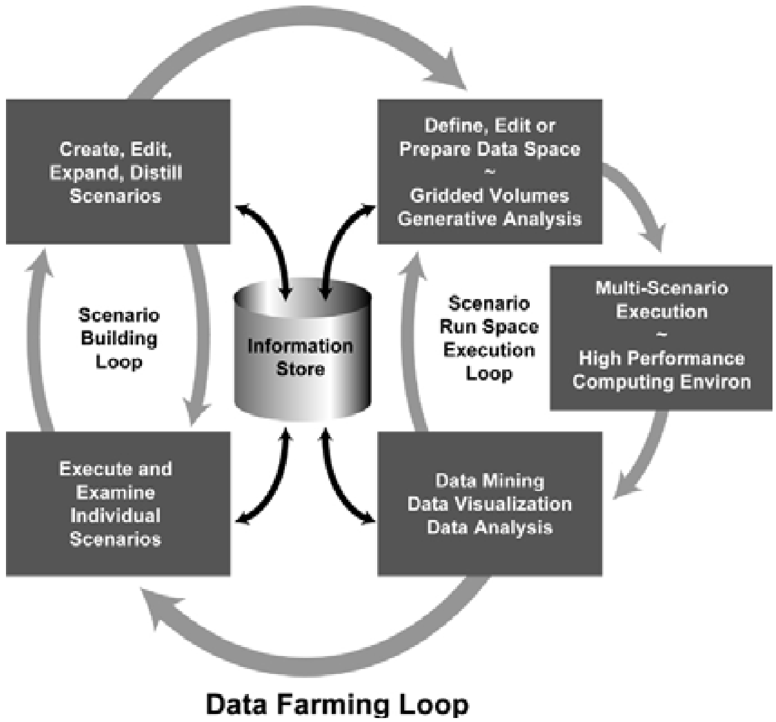

Figure 1. Iterative nature of data farming (From Horne & Meyer, 2004).

A key component of effective data farming is efficient experimental design. Design of experiments (DOE) is a field that applies a systematic approach to observing the impact of changing variables in a simulation. The application of DOE within the data farming loop in Figure 1 enables observation of single variable effects and interactions between variables. The Appendix summarizes the components constructed to implement OSAM in a data farming environment.

2. Design of Experiments

Data farming enables study of a model's response to multiple variations of many input parameters, available computing power and experimental design features magnify the benefits of data farming techniques. As one objective of this thesis is to explore the applicability of data farming to OSAM, the scope of

this experiment is limited to varying 90 parameters, as described in Tables 1–5, describing the loss adjustment factors of the Surface Warfare and Human Resources communities. All DOEs retain the mapping described in these tables, though in later experiments many input parameters remain constant at analytically determined optimal values. To assist in exploring the lateral transfer research question, analysts at OPNAV N14 adapted OSAM to add a new designator, 902x, to be defined as needed for specific research purposes. For this investigation, the 902x designator includes SWOs declined the opportunity to lateral transfer. The 902x designator has its own set of historical loss rates, distinct from SWOs who never applied for lateral transfer.

Table 1. Each input parameter to vary in OSAM simulation mapping to its description of attributes. This table shows the mapping for the loss adjustment factors in the first projection year of each simulation.

loss_adj factor mapping			
Projection Year	designator	grade	input parameter
1	HR (1200)	1	V1
		2	V2
		3	V3
		4	V4
		5	V5
		6	V6
	SWO (1110) & SWO Trainee (1160)	1	V7
		2	V8
		3	V9
		4	V10
		5	V11
		6	V12
	SWOs declined for Lateral Transfer (902x)	1	V13
		2	V14
		3	V15
		4	V16
		5	V17
		6	V18

Table 2. Mapping for the loss adjustment factors in the second projection year of each simulation.

loss_adj factor mapping			
Projection Year	designator	grade	input parameter
2	HR (1200)	1	V19
		2	V20
		3	V21
		4	V22
		5	V23
		6	V24
	SWO (1110) & SWO Trainee (1160)	1	V25
		2	V26
		3	V27
		4	V28
		5	V29
		6	V30
	SWOs declined for Lateral Transfer (902x)	1	V31
		2	V32
		3	V33
		4	V34
		5	V35
		6	V36

Table 3. Mapping for the loss adjustment factors in the third projection year.

loss_adj factor mapping			
Projection Year	designator	grade	input parameter
3	HR (1200)	1	V37
		2	V38
		3	V39
		4	V40
		5	V41
		6	V42
	SWO (1110) & SWO Trainee (1160)	1	V43
		2	V44
		3	V45
		4	V46
		5	V47
		6	V48
	SWOs declined for Lateral Transfer (902x)	1	V49
		2	V50
		3	V51
		4	V52
		5	V53
		6	V54

Table 4. Mapping for the loss adjustment factors in the fourth projection year.

loss_adj factor mapping			
Projection Year	designator	grade	input parameter
4	HR (1200)	1	V55
		2	V56
		3	V57
		4	V58
		5	V59
		6	V60
	SWO (1110) & SWO Trainee (1160)	1	V61
		2	V62
		3	V63
		4	V64
		5	V65
		6	V66
	SWOs declined for Lateral Transfer (902x)	1	V67
		2	V68
		3	V69
		4	V70
		5	V71
		6	V72

Table 5. Mapping for the loss adjustment factors in the fifth projection year.

loss_adj factor mapping			
Projection Year	designator	grade	input parameter
5	HR (1200)	1	V73
		2	V74
		3	V75
		4	V76
		5	V77
		6	V78
	SWO (1110) & SWO Trainee (1160)	1	V79
		2	V80
		3	V81
		4	V82
		5	V83
		6	V84
	SWOs declined for Lateral Transfer (902x)	1	V85
		2	V86
		3	V87
		4	V88
		5	V89
		6	V90

In a simulation environment with a small number of variable input parameters and a discrete number of levels for each parameter, it is possible to run an experiment covering every combination of variables. This set of conditions describes a full factorial design, and this type of experiment exhausts a design space, providing maximum information to an analyst. Unfortunately, it is infeasible to conduct a full factorial experiment on most real world models, and impossible for many, due to the exponential growth of design points required with the addition of each factor or factor level. Methods in the area called DOE devote resources to identifying and exploring experimental designs that cover much of the design space with a fraction of the design points that would appear in a full factorial design. Latin hypercubes (LHs) and nearly orthogonal Latin hypercubes (NOLHs) are two design types that satisfy this challenge neatly (Sanchez, 2006).

When the factors, or variables, of a DOE are columns with N rows representing the possible levels for each factor, a randomized permutation of each column results in a Latin hypercube design. This type of design is most beneficial in experiments with large numbers of factors, and a randomized LH has good orthogonality properties when the number of design points is much greater than the number of factors. For smaller designs, it is important to select a LH design with low pairwise correlation between columns. An alternative to generating multiple LHs and choosing one with low pairwise correlations is to use an NOLH design. The SEED Center at NPS maintains spreadsheets pre-built to generate NOLH designs for small and moderate numbers of factors. Even with a small number of factors to vary, a full factorial design is cumbersome with more than two levels. An NOLH design has good space-filling and orthogonality properties, does not need checking for pairwise correlations, and requires a fraction of the design points a full factorial design would need (Sanchez, 20006).

Running a large number of simulations, one for each design point, generates massive amounts of data. A relationship exists between the explanatory variables, or input parameters, and one or more response variables; determining this relationship correctly is often the goal of simulation analysis. In

1951, Box and Wilson introduce response surface methodology as a means to approximate this relationship using a second-degree polynomial. This methodology has proven effective and easy to apply to simulation analysis, even when details about the simulation process used to generate the data are unknown. Using current computing and available analytical software, a regression model allows all input parameters to enter the model as independent variables, along with the quadratic terms for each input parameter, and all possible two-way interactions between the input parameters. For an experiment with 90 input parameters, this methodology generates a regression model with an unwieldy number of terms, and additional statistical tools serve to simplify the model. A simulation analysis conducted after each DOE results in reduction of input parameters to include in the subsequent DOE if some parameters do not appear in the response surface model, or optimization of all generated models yields the same solution for some parameters.

In conducting this research, the first DOE varies 108 factors over 108 design points, and is a randomized LH design (S-plus script for Latin hypercubes, 2011). Each factor is a continuous variable, but the design generation uses 108 discrete levels for these factors. This first DOE intends to analyze variation over a six year forecast period, but base year data files for OSAM were only available as far back as 2007, so the simulation analysis was limited to a five year projection period. The variable mapping described in Tables 2–5 shows only the 90 factors contributing to the analysis. Of these 90 remaining factors, five represent 902x officers of grade O1 (Ensigns). Navy policy prohibits officers with less than two years of commissioned service from applying for lateral transfer; this policy effectively means that 902x Ensigns never appear in the model. The inclusion of these five factors in the first DOE is an oversight, and subsequent DOEs do not consider them.

The second DOE varies 65 factors over 128 design points, and is an NOLH design (Vieira, Sanchez, Kienitz, & Belderrain, 2011). The third DOE varies 29 factors over 128 design points, and is an NOLH design (Sanchez,

2005). This third DOE runs first with all 902x parameters equal to their corresponding SWO parameters, and a second time with all 902x parameters equal to values calculated in earlier analyses. Conventionally, as the number of factors in a DOE decreases, so does the number of design points needed. This research used fewer design points in earlier DOEs to explore and analyze the model within a reasonable period. All DOEs execute five times, once for each of the five base years, 2007–2011, that generate a forecast comparable to available historical data.

B. DATA HANDLING

Every design point generates about 80,000 rows of data, each representing a single officer in one projection year of the forecast period. To conduct a simulation analysis, it is necessary to condense this data into a single measure of effectiveness for each design point. The primary research focus is to assess the loss adjustments factors' impact on forecast accuracy, so the analysis compares forecast inventory to actual inventory for each year that historical data is available. Relative difference, absolute difference, or mean squared error can all be effective measures of forecast accuracy, but each of these needs to be weighted proportionately when condensing so much data into a single value. A straightforward solution is to calculate the mean absolute proportional error (MAPE) for each design point.

$$MAPE_{state} = \frac{\sum \frac{\left| actual_{state} - forecast_{state} \right|}{actual_{state}}}{N},$$

where N is the number of data points included.

In the context of this thesis, the state denoted by subscript refers to the combination of skill (SK), grade (GR), and fiscal year (FY). To calculate MAPE for each design point requires significant data manipulation. First, culling the data to extract only SWOs, HRs, and 902x officers enables matching forecast inventory with actual historical data for only the designators of interest to this

thesis. Then, the SWO community absorbs all 902x officers for comparison with historical inventory. The initial redesignation of these officers to 902x allows them to behave uniquely in OSAM, but they are still SWOs, and must be included in the total SWO inventory in evaluating forecast accuracy. The remaining data includes a SWO and HR inventory for each projection year and grade for all 90 design points. This table joins with a historical inventory table to generate $\mathrm{MAPE}_{\mathrm{FY}}$ values for each DP. The FY subscript associated with each MAPE value indicates that this value measures forecast accuracy for a specific fiscal year; each projection year OSAM generates yields a separate $\mathrm{MAPE}_{\mathrm{FY}}$ model. As the manipulation and combination of data tables proceeds, the number of rows, N, describing the data changes several times, rendering it a misleading value to include in final MAPE calculation. Instead, the traditional MAPE formula is adapted to normalize for total forecast.

$$MAPE_{FY} = \frac{\sum_{SK,GR}\left[\frac{\left|actual_{SK,GR,FY} - forecast_{SK,GR,FY}\right|}{actual_{SK,GR,FY}} \bullet forecast_{SK,GR,FY}\right]}{\sum_{SK,GR} forecast_{SK,GR,FY}}$$

The resulting data set includes one $\mathrm{MAPE}_{\mathrm{FY}}$ value for each design point, used in the next phase of analysis to generate regression models. Conducting MAPE calculations proportioned on rank and skill in this fashion ensures that a small group of officers, such as HR Captains (O6s), do not exert the same influence on the overall MAPE model as a large subset, such as SWO Ensigns (O1s). This method simultaneously ensures that the influence of deviations within a subset exert a proportional influence on the model (i.e., a forecast with five more HR Captains than historical has a greater impact on the HR Captain component than a forecast with five more SWO Ensigns than historical). This second attribute is particularly important if applying this method to modeling MAPE by designator and fiscal year ($\mathrm{MAPE}_{\mathrm{FY,SK}}$), rather than only by fiscal year ($\mathrm{MAPE}_{\mathrm{FY}}$) as implemented in this simulation analysis.

The last step in the data-handling phase of analysis is subsetting MAPE calculations by fiscal year, generating a file for each projection year with a MAPE value for each design point. Once matched with the original DOE file, this data table is ready for the modeling phase of analysis.

C. REGRESSION ANALYSIS

OSAM's forecast accuracy is a function of many complex inter-related elements, none of which exhibit linear relationship in the execution of the model. Design of experiments and simulation analysis enable reduction of the complex relationship between loss adjustment factors and forecast accuracy to regression modeling. Ordinary least squares regression is insufficient to describe this relationship, but a stepwise regression allowing all terms in a response surface model can predict MAPE effectively. A response surface includes each parameter varied in the model, quadratic terms for each variable and all two-term interactions between variables (Box & Wilson, 1951).

Using a minimum Akaike's Information Criterion (AIC) stopping rule, stepwise regression identifies the best model, based on subjective statistical rules, of MAPE for each projection year and base year; each DOE generates 15 MAPE models. The model naming convention used in this thesis is base year-MAPE-projection year, so the model named 2007MAPE1 is the MAPE model for the first projection year (FY07) of the scenario with base year 2007.

For the first DOE, the MAPE models include a large number of terms and exhibit excellent fit, many with r-square values greater than 0.98. A smaller number of terms is desirable, so this researcher employs a process that runs the model iteratively to observe t-statistics for individual model coefficients and remove additional terms manually from the stepwise model. The modeling challenge is to achieve a good enough fit while limiting the total number of terms included in the model. The solution to this challenge is to make judgment calls in balancing the AIC value and goodness of fit statistics with the likelihood that included terms are individually significant to the model. This balancing act is

simpler with later DOEs, when fewer terms in the model limit the goodness of fit, disallowing the opportunity to remove terms from the initial stepwise model.

D. OPTIMIZATION BY NONLINEAR PROGRAMMING

It is desirable to minimize the absolute deviation of forecast inventory from actual inventory, but a direct attempt to minimize MAPE, a function of loss adjustment factors, will result in most or all factors being set to their minimum allowable values. Further, it is desirable to compare multiple MAPE models simultaneously. When comparing multiple models in a group, or meta-model, the maximum MAPE among these models is the value to minimize. Approaching the problem in this manner results in most or all models in the meta-model ending with very similar MAPE values, resulting in a better solution set than could be reached by minimizing the total or average MAPE of the meta-model. This problem formulation is:

$$\min_{x \in V}\left[\max_{x \in V}(MAPE)\right]$$
$$\text{s.t. } x_{\min} \le x \le x_{\max} \;\; \forall \; x \in \{V1, V2, \ldots V90\}$$
$$MAPE \ge 0 \;\; \forall \; MAPE \in \text{ meta-model}$$

The simplest meta-model to use includes each of the fifteen MAPE models generated for the DOE. Some base year scenarios provide MAPE data for only one or two years, and only one or two models cover some projection years. To account for this uneven distribution of data and reduce the influence of any single model on the final solution set, a formulation of meta-models derives from three different grouping categories. One category includes all models generated from a given base year scenario. A second category includes all models that project a given projection year, independent of base year. A third category includes all models that predict a given fiscal year. Table 6 demonstrates the meta-model groupings considered in determining optimal values for each loss adjustment factor.

A benefit of this problem formulation is its ease of implementation in Microsoft Excel. A known limitation of Excel's solver feature is that the solution is a local minimum, but not necessarily a global minimum. The solution set returned by Excel is dependent on the initial values selected for all variables. For this reason, the initial values chosen were consistent and equal to 1.0 for all loss adjustment factors. This practice does not guarantee the smallest possible MAPE value, but the potential errors due to this software property are smoothed by the averaging of all results over the fifteen meta-models described in Table 6.

Table 6. This table demonstrates the meta-model groupings considered in determining optimal values for each loss adjustment factor. The model naming convention used is base year-MAPE-projection year, so the model 2007MAPE1 is the MAPE model for the first projection year (FY07) of the scenario with base year 2007. The MAPE values in this table are for demonstration purposes only.

grouped according to base year	
2007 scenario summary	
model	MAPE
2007MAPE 1	0.12369
2007MAPE 2	0.16065
2007MAPE 3	0.02441
2007MAPE 4	0.00708
2007MAPE 5	0.11844
max	0.16065
2008 scenario summary	
model	
2008MAPE 1	0.08931
2008MAPE 2	0.05747
2008MAPE 3	0.06707
2008MAPE 4	0.18762
max	0.18762
2009 scenario summary	
model	
2009MAPE 1	0.12875
2009MAPE 2	0.09360
2009MAPE 3	0.13666
max	0.13666
2010 scenario summary	
model	
2010MAPE 1	0.10380
2010MAPE 2	0.06817
max	0.10380
2011 scenario summary	
model	
2011MAPE 1	0.16239
max	0.16239

grouped according to projection year being forecast (independent of base year)	
MAPE 1 summary	
model	MAPE
2007MAPE 1	0.12369
2008MAPE 1	0.08931
2009MAPE 1	0.12875
2010MAPE 1	0.10380
2011MAPE 1	0.16239
max	0.16239
MAPE 2 summary	
model	
2007MAPE 2	0.16065
2008MAPE 2	0.05747
2009MAPE 2	0.09360
2010MAPE 2	0.06817
max	0.16065
MAPE 3 summary	
model	
2007MAPE 3	0.02441
2008MAPE 3	0.06707
2009MAPE 3	0.13666
max	0.13666
MAPE 4 summary	
model	
2007MAPE 4	0.00708
2008MAPE 4	0.18762
max	0.18762
MAPE 5 summary	
model	
2007MAPE 5	0.11844
max	0.11844

grouped according to fiscal year being forecast	
MAPE2007 summary	
model	MAPE
2007MAPE 1	0.12369
max	0.12369
MAPE2008 summary	
model	
2007MAPE 2	0.16065
2008MAPE 1	0.08931
max	0.16065
MAPE 2009 summary	
model	
2007MAPE 3	0.02441
2008MAPE 2	0.05747
2009MAPE 1	0.12875
max	0.12875
MAPE 2010 summary	
model	
2007MAPE 4	0.00708
2008MAPE 3	0.06707
2009MAPE 2	0.09360
2010MAPE 1	0.10380
max	0.10380
MAPE 2011 summary	
model	
2007MAPE 5	0.11844
2008MAPE 4	0.18762
2009MAPE 3	0.13666
2010MAPE 2	0.06817
2011MAPE 1	0.16239
max	0.16239

A solution for each of the meta-models in Table 6 determines the set of loss adjustment factors that minimizes the maximum MAPE in the meta-model. An overall meta-model including all 15 MAPE models also produces a solution set. These 16 solution sets demonstrate a range of values for each loss adjustment parameter. As discussed earlier, some parameters do not appear in every meta-model, but this process guarantees at least four data points for every loss adjustment factor. Only one MAPE model, 2007MAPE5, depends on the values of parameters V73 – V90. The optimization of the three meta-models in Table 6 including 2007MAPE5, as well as the overall meta-model, provide a solution set for these 18 factors, one data point from each solution set. Similarly, parameters V55 – V72 appear only in models 2007MAPE4, 2007MAPE5, and 2008MAPE4, so these variables appear in seven solution sets, and their final recommended values depend on the seven data points available for each parameter in this range. These data points determine an average value and 95% confidence interval (CI) for each loss adjustment factor. The CI width for every factor informs the decision to hold it constant in subsequent experiments or retain it as an input parameter.

The processes described in this chapter apply to analysis of data collected from each DOE, and the results from the first two DOEs used to formulate the subsequent DOE. This iterative data farming loop produces results that answer the research questions put forth in this thesis. Chapter IV presents a summary of these results.

IV. ANALYSIS OF EXPERIMENTAL RESULTS

This chapter presents the computational results derived from each design of experiments and discusses the process of deriving subsequent experimental designs. This chapter also presents results of the final experiments, discusses the implications of these results, and assesses the statistical and practical significance of findings.

A. FIRST DESIGN OF EXPERIMENTS

1. Loss Adjustment Factors to Hold Constant

A solution for each of the meta-models in Table 6 determines the set of loss adjustment factors that minimizes the maximum MAPE in the meta-model. An overall meta-model including all 15 MAPE models also produces a solution set. These 16 solution sets demonstrate a range of values for each loss adjustment parameter. As discussed earlier, some parameters do not appear in every meta-model, but this process guarantees at least four data points for every loss adjustment factor.

This analysis calculates an average value and 95% confidence interval (CI) for each loss adjustment factor. The factors for projection year five have the fewest number of data points, and thus have the widest confidence intervals, as a rule. A summary table of average values, the CI lower bound (LB), and CI upper bound (UB) for each factor indicates which parameters are constant in the next DOE. A rule of thumb used is to hold constant factors with a CI smaller than 0.1, or special cases of factors that do not vary much, despite having a large CI. Table 7 includes factors determined by DOE1 to be constant in DOE2. The factors and confidence intervals in Table 7 are final determined values, and appear again in the graphical summary of results later in this chapter.

Table 7. Factors to hold constant in DOE2, based on DOE1 analysis. Shaded cells have a CI wider than 0.1. V38 is held constant for DOE2 because 9 of 11 values for V38 were equal, with outliers heavily influencing CI calculation.

Projection Year	designator	grade	input parameter	average	95% Confidence interval	
					LB	UB
2	HR	6	V24	1.039	1.024	1.054
	902x	2	V32	1.000	0.999	1.001
3	HR	2	V38	1.208	1.058	1.359
	SWO	5	V47	1.000	0.999	1.001
	902x	3	V51	1.000	1.000	1.000
4	HR	4	V58	1.000	1.000	1.000
		5	V59	1.000	1.000	1.000
		6	V60	1.000	1.000	1.000
	SWO	1	V61	1.000	1.000	1.000
		6	V66	1.000	1.000	1.000
	902x	2	V68	1.000	1.000	1.000
		3	V69	1.000	1.000	1.000
5	HR	1	V73	1.000	1.000	1.000
		2	V74	1.000	1.000	1.000
		5	V77	1.000	1.000	1.000
		6	V78	1.000	1.000	1.000
	SWO	2	V80	1.000	1.000	1.000
	902x	2	V86	1.000	1.000	1.000
		3	V87	1.000	1.000	1.000
		4	V88	1.000	1.000	1.000

2. Selection of Parameter Ranges for DOE2

The factors not included in Table 7 remain variable input parameters in the second design of experiments (DOE2). After analysis of DOE1, some factors have a 95% CI greater than the size of the original range allowed in the experiment. The two-fold purpose of DOE1 is to identify variables to hold constant in subsequent experiments, and to reduce the range of remaining input parameters to vary in DOE2. With this in mind, the range allowed for each remaining variable is a maximum of 0.2. The center of each variable’s range is its average value determined from DOE1 analysis, with a range of 0.2 or its 95% CI, whichever is smaller.

B. SECOND DESIGN OF EXPERIMENTS

1. Loss Adjustment Factors to Hold Constant

As in analysis of DOE1, the results of DOE2 yield a solution for each of the meta-models in Table 6, and an overall meta-model including all 15 MAPE models. Taken together, these solution sets determine the set of loss adjustment factors that minimizes the maximum MAPE in the meta-model. Descriptive statistics for these 16 solution sets determine an average value and a 95% CI for each loss adjustment factor. A summary table of values and CIs for each factor indicates which factors are constant in the next DOE. A rule of thumb used is to hold constant factors with a CI smaller than 0.1. Table 8 displays all loss adjustment factors to be held constant in DOE3, in addition to those indentified in Table 7. The shaded rows in Table 8 indicate parameters held constant in DOE3, despite a CI wider than 0.1. Each of these parameters is a 902x loss adjustment factor, held constant in DOE3 to test the secondary hypothesis of this thesis: using distinct values for 902x loss adjustment factors determined from a rigorous analysis yields a more accurate forecast than applying SWO loss adjustment factors to 902x officers. The factors and confidence intervals in Table 8 are final determined values, and appear again in the graphical summary of results later in this chapter.

2. Selection of Parameter Ranges for DOE3

The factors not included in Table 7 or Table 8 remain variable input parameters in the third design of experiments (DOE3). The analysis of DOE2 identifies variables to hold constant in subsequent experiments, and to reduce the range of remaining input parameters to vary in DOE3. With this in mind, all SWO and HR loss adjustment factors with a CI wider than 0.1 remain variable in DOE3. All 902x loss adjustment factors are constant in DOE3, to test the secondary hypothesis of this thesis: using distinct values for 902x loss

adjustment factors determined from a rigorous analysis yields a more accurate forecast than applying SWO loss adjustment factors to 902x officers.

Table 8. Factors to hold constant in DOE3, based on analysis of DOE2. Shaded cells have CI wider than 0.1, but remain constant in the next DOE at their average values, for the sole purpose of testing the secondary hypothesis: that experimentally determined factors for 902x will yield a better forecast than using the SWO factors for 902x.

Projection Year	designator	grade	input parameter	average	95% Confidence interval LB	95% Confidence interval UB
1	HR	1	V1	1.001	0.985	1.018
		2	V2	1.004	0.972	1.035
	902x	2	V14	0.970	0.812	1.127
		3	V15	1.051	0.882	1.220
		4	V16	1.012	0.945	1.079
		5	V17	1.000	0.964	1.035
		6	V18	0.996	0.937	1.055
2	HR	2	V20	1.067	1.051	1.083
		3	V21	1.087	1.074	1.099
	SWO	3	V27	0.883	0.857	0.909
	902x	3	V33	1.015	0.980	1.049
		4	V34	1.019	0.963	1.075
		5	V35	1.036	0.991	1.082
		6	V36	1.016	1.013	1.019
3	HR	1	V37	1.078	1.078	1.078
		4	V40	1.046	1.030	1.061
		5	V41	1.063	1.059	1.067
		6	V42	1.077	1.067	1.086
	SWO	1	V43	1.045	1.016	1.075
		4	V46	1.047	1.011	1.084
		6	V48	1.072	1.072	1.072
	902x	2	V50	1.078	1.051	1.105
		4	V52	1.079	1.067	1.090
		5	V53	1.016	0.982	1.050
		6	V54	1.014	0.979	1.049
4	HR	1	V55	1.075	1.075	1.075
		2	V56	1.118	1.100	1.135
		3	V57	1.149	1.149	1.149
	SWO	4	V64	1.101	1.098	1.104
	902x	4	V70	1.110	1.110	1.110
		5	V71	1.097	1.075	1.120
		6	V72	1.141	1.056	1.225
5	HR	4	V76	1.116	1.116	1.116
	SWO	1	V79	1.183	1.183	1.183
		6	V84	1.209	1.209	1.209
	902x	5	V89	1.094	1.094	1.094
		6	V90	1.119	1.119	1.119

The remaining 28 SWO and HR loss adjustment factors vary in DOE3 according to an NOLH design. The 128 runs of this design execute twice; DOE3a assigns to all 902x loss adjustment factors the value determined in analysis of DOE1 and DOE2, while DOE3b sets each 902x loss adjustment factor equal to the SWO loss adjustment factor for the same projection year and grade combination.

C. THIRD DESIGN OF EXPERIMENTS

1. Use of Unique Loss Adjustment Factors for Declined Lateral Transfer Applicants

The null hypothesis for this comparison is the secondary hypothesis specified in Chapter I of this thesis: that using distinct values for 902x loss adjustment factors determined from a rigorous analysis yields a more accurate forecast than applying SWO loss adjustment factors to 902x officers. A paired two sample t-test is sufficient to test this hypothesis. The results of this t-test, displayed in Table 9, indicate that using experimentally determined 902x loss adjustment factors does not provide a more accurate forecast, as measured by MAPE, than setting all 902x factors equal to their corresponding SWO factors, at a 95% confidence level.

Table 9. t-Test: Paired Two Sample for Means, to test secondary hypothesis: using distinct values for 902x loss adjustment factors determined from a rigorous analysis yields a more accurate forecast (smaller MAPE) than applying SWO loss adjustment factors to 902x officers.

	DOE3a	*DOE3b*
Mean	0.1038115	0.09837249
Variance	0.00071632	0.00057733
Observations	16	16
Pearson Correlation	0.93988152	
Hypothesized Mean	0	
df	15	
t Stat	2.50570874	
P(T<=t) one-tail	0.01134058	
t Critical one-tail	1.73960672	

This important result indicates there is no benefit to implementing a distinct set of loss adjustment factors for SWOs declined a lateral transfer. Notably, OSAM models historical loss rates differently for 902x officers than for SWOs who have not applied for a lateral transfer. Thus, disproval of this secondary research hypothesis does not mean there is no benefit to modeling 902x officers distinctly from SWOs. Additional model exploration may offer a conclusive answer to this question.

2. Final Values for Loss Adjustment Factors

As in earlier phases of analysis, a solution for each of the meta-models in Table 6, and an overall meta-model including all 15 MAPE models, determines the set of loss adjustment factors that minimizes the maximum MAPE in the meta-model. Subsequent to disproval of the secondary research hypothesis, analysis DOE3b recommends appropriate factor values for future forecasting, disregarding results from DOE3a. Descriptive statistics for the 16 solution sets of DOE3b determine an average value and a 95% CI for each loss adjustment factor. A summary table of values and CIs for each factor indicates final recommended values of loss adjustment factors, and their respective confidence intervals (See Table 10). The shaded rows in Table 10 indicate parameters with a CI wider than 0.15. Additional experiments might narrow these ranges further, but the reduction in parameters varied through this iterative analytical process led to difficulty generating acceptable regression models. This research instead recommends accepting these average values, with a note of caution. The factors and confidence intervals in Table 8 are final determined values, and appear again in the graphical summary of results later in this chapter.

Taken together, the values in Tables 7–8 and Table 10 are the experimental results determined for use in future forecasting efforts with OSAM.

Table 10. Factor values determined by analysis of third and final DOE. Shaded cells have CI wider than 0.15.

Projection Year	designator	grade	input parameter	average	95% Confidence interval	
					LB	UB
1	HR	3	V3	0.981	0.938	1.024
		4	V4	0.984	0.919	1.050
		5	V5	1.031	0.961	1.101
		6	V6	1.020	0.976	1.064
	SWO	1	V7	1.028	0.908	1.147
		2	V8	0.997	0.897	1.096
		3	V9	0.974	0.905	1.043
		4	V10	0.999	0.903	1.096
		5	V11	0.987	0.903	1.072
		6	V12	0.961	0.828	1.095
2	HR	1	V19	1.020	1.018	1.022
		4	V22	0.999	0.960	1.038
		5	V23	0.983	0.957	1.010
	SWO	1	V25	0.991	0.955	1.028
		2	V26	1.000	0.942	1.057
		4	V28	1.008	0.972	1.043
		5	V29	1.004	0.931	1.077
		6	V30	1.014	0.966	1.061
3	HR	3	V39	1.092	1.005	1.179
	SWO	2	V44	1.042	1.042	1.042
		3	V45	0.874	0.794	0.954
4	SWO	2	V62	0.961	0.912	1.009
		3	V63	0.936	0.831	1.042
		5	V65	0.992	0.963	1.021
5	HR	3	V75	1.101	1.082	1.119
	SWO	3	V81	0.902	0.834	0.969
		4	V82	1.017	0.981	1.054
		5	V83	1.173	1.173	1.173

3. Interpretation of Results

The final experimental values displayed in Tables 7–8 and Table 10 are useful for implementation in OSAM, but a list of numbers is only one demonstration of how the recommendations of this research compare to the values used in OSAM runs prior to this analysis. Figure 2 is a visual representation of the 95% CIs for SWO loss adjustment factors, overlaid with the

null hypothesis (primary hypothesis 1) and the working hypothesis (primary hypothesis 2). The vertically aligned diamonds on this plot each represent the upper and lower bound of the CI for the case indicates on the horizontal axis. Figure 2 shows that the CI for many SWO loss adjustment factors contains either one or both hypothetical values, with some notable exceptions.

The O3, or Lieutenant, average loss adjustment factors recommended by this analysis fall below the null and working hypothesis for all projection years, with the working hypothesis values falling completely outside the CI for projection years two through five, and the null hypothesis values falling completely outside the CI for projection years two, three, and five. This result could be due to a tendency of OSAM to overestimate O3 loss rates, leading to a recommendation for O3 loss adjustment factors less than 1.0 across all projection years. This finding may suggest a need to revisit the method of estimating O3 loss rates in OSAM, but more likely identifies a specific issue with SWOs, because the same behavior does not occur in the HR community (See Figure 3).

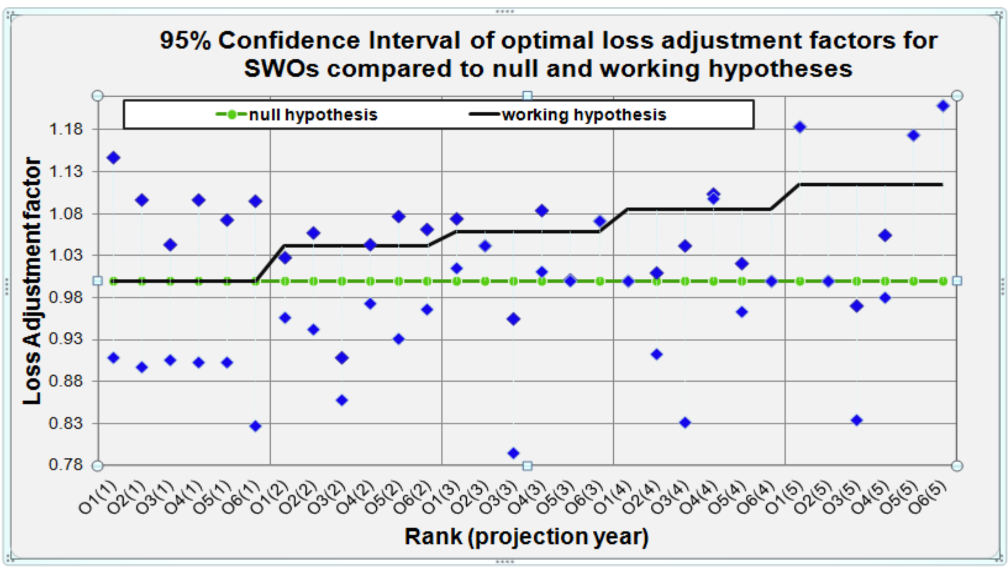

Figure 2. Ninety-five percent confidence intervals of optimal loss adjustment factors for SWOs compared to null and working hypotheses. Diamonds indicate upper and lower bound of respective CIs.

Figure 3 is a visual representation of the 95% CIs for HR loss adjustment factors, overlaid with the null hypothesis (primary hypothesis 1) and the working hypothesis (primary hypothesis 2). The vertically aligned diamonds on this plot each represent the upper and lower bound of the CI for the case indicates on the horizontal axis. Figure 3 shows that the CI for many HR loss adjustment factors contains either the null or working hypothesis value. The HR factor values align closely with the working hypothesis values, with the exception of several values in projection years four and five eliminated from further variation early in analysis because they did not appear in any regression models.

Figure 3 suggests that OSAM may be overestimating loss rates for HR O2s and O3s in projection years two and four, and underestimating loss rates for HR O1s, O4s, and O5s in projection year two. While the deviations from hypothetical values are not as large as for SWOs, there is evidence to suggest forecast accuracy improves when using the experimentally determined loss adjustment factors, particularly in years two and four.

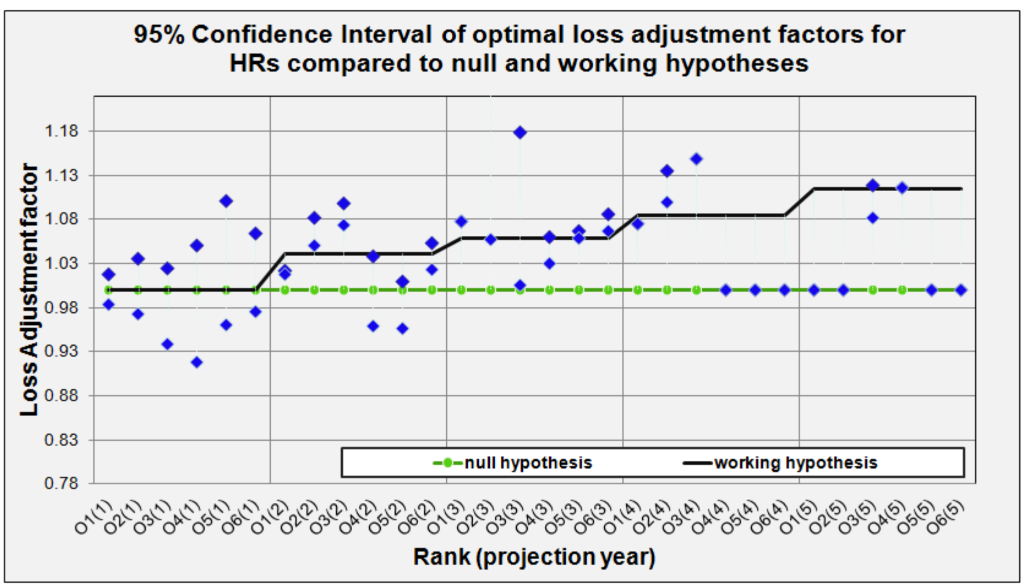

Figure 3. Ninety-five percent confidence intervals of optimal loss adjustment factors for HRs compared to null and working hypotheses. Diamonds indicate upper and lower bound of respective CIs.

The number of HR officers is significantly smaller than the number of SWOs at any given time. This analysis determines the loss adjustments factors displayed in Figures 2 and 3 simultaneously. The focus of this thesis is overall MAPE for the conglomerate of officer communities considered, but determination of loss adjustment factors one designator at a time could result in detailed information for specific communities. Development of regression models for MAPE separated by designator will yield this information.

D. VERIFICATION EXPERIMENT

A final experiment runs with only three design points. The first DP sets all loss adjustment factors of interest equal to 1.0, to test primary hypothesis 1, referred to in Figures 2 and 3 as the null hypothesis. The second DP sets loss adjustment factors for projection year one equal to 1.0, 1.041 in year two, 1.059 in year three, 1.085 in year four, and 1.114 in year five, to test primary hypothesis 2, referred to in Figures 2 and 3 as the working hypothesis. The third DP sets all loss adjustment factors equal to the average values reported in Tables 7–8 and Table 10. Each of these DPs provides 15 MAPE values, one for each base year/projection year combination. These three sets of MAPE values, shown in Table 11, are comparable to one another for hypothesis testing.

Table 11. Summary of MAPE values from final set of OSAM runs.

		MAPE		
baseyear	projection year	hypothesis 1	hypothesis 2	Experimental Results
2007	2007	0.03994	0.03994	0.04063
2007	2008	0.05722	0.05793	0.0649
2007	2009	0.08593	0.0876	0.09325
2007	2010	0.1308	0.13008	0.11542
2007	2011	0.16801	0.17947	0.15208
2008	2008	0.05485	0.05485	0.05305
2008	2009	0.07957	0.07965	0.08988
2008	2010	0.10263	0.1096	0.09576
2008	2011	0.16301	0.16365	0.14534
2009	2009	0.07982	0.07982	0.07822
2009	2010	0.11527	0.11616	0.114
2009	2011	0.16658	0.16481	0.15079
2010	2010	0.09616	0.09616	0.09363
2010	2011	0.12217	0.12119	0.12048
2011	2011	0.10249	0.10249	0.10633

1. Test of Hypothesis 1

The null hypothesis for this comparison is that the MAPE generated from experimental results is not smaller than the MAPE generated from a set of loss adjustment factors in which all values are 1.0. A paired two sample t-test is sufficient to test this hypothesis. The results of this t-test, displayed in Table 12, indicate that experimental results provide a better forecast than setting all loss adjustment factors equal to 1.0, at a 90% confidence level.

Table 12. t-Test: Paired Two Sample for Means, to test primary hypothesis 1: the MAPE generated from experimental results is not smaller than the MAPE generated from a set of loss adjustment factors in which all values are 1.0.

	Experimental Results	*hypothesis 1*
Mean	0.100917333	0.104296667
Variance	0.001133595	0.001639373
Observations	15	15
Pearson Correlation	0.986185896	
Hypothesized Mean Difference	0	
degrees of freedom	14	
t Stat	**-1.426505455**	
P(T<=t) one-tail	**0.087820762**	
t Critical one-tail	1.761310115	

2. Test of Hypothesis 2

The null hypothesis for this comparison is that the MAPE generated from experimental results is not smaller than the MAPE generated from a set of loss adjustment factors in which values for projection year one are equal to 1.0, year two values are 1.041, year three values are 1.059, year four values are 1.085, and year five values are 1.114. Again, a paired two sample t-test is sufficient to test this hypothesis. The results of this t-test, displayed in Table 13, indicate that experimental results provide a better forecast than applying OPNAV N14's loss adjustment factors describing a slowly improving economy (setting values for projection year one equal to 1.0, year two values are 1.041, year three values are 1.059, year four values are 1.085, and year five values are 1.114.), at a 90% confidence level.

Table 13. t-Test: Paired Two Sample for Means, to test primary hypothesis 2: the MAPE generated from experimental results is not smaller than the MAPE generated from a set of loss adjustment factors describing a slowly improving economy.

	Experimental Results	*hypothesis 2*
Mean	0.100917333	0.10556
Variance	0.001133595	0.00173016
Observations	15	15
Pearson Correlation	0.982063123	
Hypothesized Mean Difference	0	
degrees of freedom	14	
t Stat	**-1.691014156**	
P(T<=t) one-tail	**0.056482551**	
t Critical one-tail	1.761310115	

The designs of experiments used in this thesis target analysis of data from base years 2007 through 2011, and this thesis has proven that changing loss adjustment factor values can generate a better forecast (measured by MAPE) than applying the same values to all loss adjustment factors. It is desirable to test these results against forecasts not included in the original analysis, but at this time additional data is unavailable. Nonetheless, this research demonstrates the benefits of applying data farming to OSAM, both to validate the model and improve it for future use. The fifth and final chapter of this thesis delineates significant findings and suggestions for future research.

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V. CONCLUSIONS AND RECOMMENDATIONS

This thesis demonstrates the potential to assess and improve OSAM with insights provided through data farming. This chapter summarizes specific findings related to SWO and HR loss adjustment factors, and suggests direction for further exploration of OSAM's input parameters. OSAM utilizes input parameters contained in 60 database files; while this research varied a relatively small number of parameters in only one of those files, the methods employed to measure accuracy, generate a better forecast, and test specific research questions lay the foundation for countless further applications to OSAM and to other models owned by OPNAV N14. This thesis takes necessary first steps to explore the applicability of data farming, and the results suggest numerous applications for future research to undertake.

A. SIGNIFICANT FINDINGS

1. Assessment of Loss Rate Variation

OSAM implements loss rate variation over a forecast period through the multiplication of historical loss rates by a loss adjustment factor. There is a potential to model unique loss adjustment factors for each combination of designator, projection year, and years of commissioned service (YCS). The rigorous numerical analysis in this thesis comparing simulation forecasts to historical inventories confirms that in many cases, officer loss rates next year will be similar to loss rates this year. The average experimentally determined SWO and HR loss adjustment factors for the first projection year range between 0.961 and 1.031, and the 95% confidence interval includes the value 1.0 for every analyzed loss adjustment factor. This finding is in keeping with common practice in running OSAM simulations.

Forecast analysis in projection years two through five yields less consistent results across the set of HR and SWO loss adjustment factors varied.

Recommended SWO Lieutenant (O3) loss adjustment factors are less than 1.0 in every projection year, and multiple recommended values are very close to 1.0 even in later projection years. For loss adjustment factors that deviate from 1.0, there seems to be a general upward trend with increasing projection years.

2. Validation of Results

This research delivers a suggested value to apply for each factor in future OSAM runs, and provides a CI for these factors. The complex interactions between officer communities, ranks, and overall inventory make validation of individual loss adjustment factors impractical. A validation of the entire solution set is feasible, and demonstrates that experimentally determined loss adjustment factors yield a better forecast than holding parameters constant equal to 1.0, at a 90% confidence level. This validation also affirms that experimental results yield a better forecast than varying all factors identically in each projection year according to OPNAV N14's set of loss adjustment factors describing a slowly improving economy (1.0 in year one, 1.041 in year two, 1.059 in year three, 1.085 in year four, and 1.114 in year five), again at a 90% confidence level.

3. Loss Rate Variation for Declined Lateral Transfer Applicants

As part of this research, a modification of OSAM adds a fictitious designator, 902x. This designator is adaptable to pursue various research questions, and for this thesis represents SWOs declined the opportunity to lateral transfer. Analysis of the first two experimental designs determines optimal values for 902x loss adjustment factors, and the final design of experiments executed twice, once with these experimentally determined values, and once with all 902x factors equal to their corresponding SWO factors. Analysis of this experiment reveals that there is no need to model loss adjustment factors differently for declined lateral transfer applicants. In fact, using the experimentally determined

902x values does not provide a more accurate forecast, as measured by MAPE, than applying the appropriate SWO values to these factors, at a 95% confidence level.

This result at first seems counterintuitive, since earlier research (Kleyman & Parcell, 2010) shows that SWOs declined the opportunity to lateral transfer are more likely to leave the Navy than SWOs who never applied for lateral transfer. With this background in mind, it is important to recall that this hypothesis test indicates there is no benefit to varying loss adjustment factors distinctly for 902x officers, but does not consider the underlying loss rates built into the model. Notably, OSAM models 902x officers with unique historical loss rates, so this interesting finding is insufficient to suggest eliminating the 902x designator from the model.

4. Applicability of Data Farming to OSAM

One objective of this thesis is to explore the potential for continued application of data farming techniques to officer inventory projection. OSAM's adaptation for use in a data farming environment enabled multiple simulations to run without operator interaction. This capability provides an opportunity to run countless variations of experimental designs in future explorations of the model. Data farming is unquestionably a useful technique for exploring OSAM.

B. RECOMMENDATIONS FOR FUTURE RESEARCH

1. Additional Base Years

A noted limitation of this research is the lack of aligning forecast and historical data for early fiscal years and later projection years in the time period observed. The analytical approach employed adjusts for this information shortage by considering overlapping meta-models. The analysis of forecasts for additional base years is an ideal solution to this data scarcity. In addition to improving the accuracy of results, an expansion of this thesis to additional base

years provides an opportunity to observe forecast variation over additional economic and political environments, which may influence the retention behavior of some Navy officers.

Analysis of forecast accuracy over a longer time period should reduce the number of meta-models needed to determine recommended loss adjustment factors. Additional data for each meta-model should also enable assessment of which set of meta-model groupings is most effective in determining recommended loss adjustment factors. An exploration of meta-models is particularly useful to OPNAV N14, as this methodology may apply to future versions of OSAM as a built-in accuracy check.

2. Modeling Distinct Loss Rates for Declined Lateral Transfer Applicants

This research concludes there is no need to model loss adjustment factors for declined lateral transfer applicants uniquely from the loss adjustment factors of officers who did not apply from lateral transfer. A logical next step is to assess whether there is value in modeling these declined lateral transfer applicants as a unique designator at all. As noted previously, OSAM models 902x officers with unique historical loss rates. The implementation of the 902x designator in OSAM is at the user's discretion, and its definition is alterable according to the researcher's needs. Running a DOE twice (once with 902x historical loss rates determined appropriately for SWOs declined the opportunity to lateral transfer, and once with 902x historical loss rates equal to corresponding SWO historical loss rates), will provide the data necessary to resolve this research question. Past research suggests these officers have unique promotion and loss probabilities. Application of data farming to this problem can determine whether these differences are significant enough to warrant modeling a unique designator. Application of this methodology to additional officer communities may determine which, if any, communities benefit from modeling this category of officers uniquely.

3. Additional Designators

This research studies the loss adjustment factors for four of the 74 designators modeled by OSAM. There is value in repeating this study for other designators. The methodology applied in this thesis is appropriate to recommend loss adjustment factors for the designators studied, but all officer communities interact in OSAM to meet the total inventory requirements imposed on the entire Navy Officer Corps. A similar study encompassing more designators may recommend different values for the loss adjustment factors studied in this thesis, due to such interactions. Data farming methods are ideal for tackling this type of problem expansion, enabling exploration of a complex, unwieldy design space.

Data farming methods continue to evolve, and there are some potential limitations imposed by computing power and designs of experiments for large numbers of input parameters. OSAM includes 2,025 loss adjustment factors, and the variation of all factors simultaneously may present challenges in these areas. Exploration of the design space is possible without unique variation of all 2,025 factors, with information about which designators have loss rates that vary similarly from year to year. Grouping designators together by categories of similar behavior could enable a study of all loss adjustment factors simultaneously. For instance, it may be appropriate to assign the same loss adjustment factors to all Limited Duty Officers (LDOs), a separate set of loss adjustment factors to all nurses and Medical Service Corps (MSC) officers, and yet another set of loss adjustment factors to all Restricted Line (RL) officers. A numerically determined solution set for all loss adjustment factors in OSAM could greatly improve the forecast accuracy of mid-term inventory projections.

4. Model MAPE by Designator

This thesis assesses the quality of forecasts by measuring mean absolute proportional error (MAPE), proportioned on rank. Application of this measure of effectiveness to more specific modeling may yield additional findings of interest to both OPNAV N14 and individual officer communities. For example,

proportioning MAPE on both designator and rank would enable the building of separate SWO and HR MAPE models. Both sets of models should still include loss adjustment factors from both communities, as their inventories interact during the simulation. The unique solution sets generated from this additional analysis may provide insight on the loss behavior of individual communities, and can identify the optimal set of loss adjustment factors for a goal of maximizing forecast accuracy of a single officer community. Similarly, both communities' models could be considered together, weighting the MAPE models appropriately according to the Navy's need to meet one community's inventory needs more than another. This task requires significant input from Navy personnel subject matter experts, or consideration of many different weighting combinations. This approach to analysis has great potential for informing policy decisions, but the selection of appropriate weights for different officer communities is certain to vary widely between subject matter experts.

5. Weighting Forecast Accuracy

Accurate projection of Navy officer inventory is a goal of OSAM, and this thesis focuses on enhancing efforts to achieve this objective. In addition to overall forecast accuracy, there are many officer inventory goals that individual communities strive to meet. For instance, the SWO community needs a minimum number of Lieutenants at seven YCS to fill department head afloat billets; SWO accession plans intend to meet this need, even though this may result in more Ensigns than needed in the interim (Monroe & Cymrot, 2004). Data farming OSAM and analyzing MAPE calculations for very specific combinations of officer attributes can potentially improve projection to meet such specific goals.

C. IMPACT OF RESEARCH

OPNAV N14 gleans multiple benefits from this research, both in the short term and the long term. Analysts at N14 have envisioned building an automated validation or accuracy check capability into current and future forecasting

models, and will explore the use of MAPE as a forecast accuracy metric. The methodology utilized in this thesis seems a promising means of accomplishing this goal.

This research highlights some weaknesses of OSAM that N14 can improve upon. One recommendation of this study is to include more historical data to adequately measure accuracy; N14 plans to make this a requirement in future model development. This thesis also identifies OSAM's overestimation of SWO Lieutenant loss rates in all projection years. The loss estimation process is a key step in personnel forecasting, and N14 strives to model losses well. The next update of OSAM will strive to correct this weakness, either including more explanatory historic information (e.g., years of total service), or using new rate generation techniques (e.g., machine learning, Bayesian, or agent-based behavioral models).

To leverage the conclusion that forecast accuracy can improve with experimentally determined loss adjustment factors, N14 will ensure that future models retain the capability for users to modify loss rates. This potential benefit lends itself to future research, particularly the investigation of loss rates for additional specific officer communities.

This thesis, the first application of data farming concepts to OSAM, lays the groundwork for continuing efforts in this area. The conclusions of this research provide actionable steps for OPNAV N14 to pursue. Further, the implementation of designs of experiments, selection of a forecast accuracy metric, and development of a multi-faceted analytical approach employed in this study serve as a roadmap for future exploration of OSAM.

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APPENDIX

This appendix describes the data farming components used to data farm OSAM. The information included here is derived from the notes of Stephen Upton, who developed the code used and executed all experiments in this thesis on the computer clusters of the SEED Center for Data Farming.

The current implementation of data farming OSAM is a limited version, in that the development of code and other artifacts is specifically to assist in completion of this thesis. The hard coding of some settings supports timely implementation of OSAM in a data farming environment. In particular, the design points used in the experiments varied only factors in the loss_adj.dbf file, based on settings for fiscal year, grade, and designator. Using the current implementation, one can vary a factor for any combination of fiscal year, grade, or designator contained in the loss_adj.dbf file. Extension of data farming to varying factors in any other input file will require editing the implementation code.

OSAM simulations run via a Microsoft Visual Fox Pro Version 9 (VFP9) executable file. An additional VFP9 file, dfosam.exe, assists in data farming OSAM. A licensed copy of VFP9 is necessary to edit the OSAM input files, as indicated by designs of experiments. In addition to this new VFP9 executable file, several other elements are part of the vital infrastructure for data farming OSAM. Table 14 provides a summary of these components.

Each OSAM run saves the output files, Multi-Year Summary.dbf and flow_pt.dbf, in a directory named for the appropriate design point. These are the files containing data to be processed and analyzes as described in Chapter III.

Table 14. Summary of components utilized in the implementation of OSAM in a data farming environment.

Component	Description
stage.OSAM.run.R	this code creates the Output and submit directories, then creates a DP_X directory for all DPs in the design, where X is the design point or row number of the DOE file. It then creates condor_submit files for all the DPs and puts them in the submit directory. (this code needs 4 arguments: [1] study.dir is the directory location, [2] basecase.name is the zipped contents of an OSAM scenario, including the OSAM executable file, [3] start.year, [4] doe.file.name)
submit-template.data	this is the condor submit template, with BASECASE STARTYEAR DOEFILE DPNUM and STUDY variables that get replaced with appropriate values by stage.OSAM.run.R code
dfOSAM.R	Generates the appropriate factors.csv file used by dfosam.exe using the factor.map.csv file, the baseyear, startyear, and DP number as input
dfosam.exe	short VFP9 executable that updates the loss_adj.dbf file based on the factors.csv file
dfOSAM.bat	calls dfOSAM.R, dfosam.exe and the OSAM executable in proper order of execution on the compute node

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